Growth Accounting in Open Economies with Distortions

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[Preliminary version: May 15, 2024]

Abstract

We present a theory for growth accounting in open economies with distortions. In addition to domestic distortions, we include distortions from imported intermediate inputs and from exports. We show that trade can influence aggregate TFP growth through three channels: the distortion of exports, the production network propagation of import distortions and through how imports are accounted for in national accounts. We quantify these forces by using administrative firm-to-firm and tax data for the universe of formal firms from Chile between 2005 and 2021. Observed TFP growth is explained by allocative efficiency rather than technological change. International trade accounts for 48% of aggregate TFP growth, with all three channels being quantitatively important.

*We thank Hugo Hopenhayn, Michael Rubens, John Asker, Andy Atkeson, David Baqaee, Ariel Burstein, Pablo Fajgelbaum, Oleg Itskhoki, Sofía Bauducco, Juan Guerra and seminar participants at Midwest Macro Fall 2022 meetings, UC San Diego SOCAE 2022, Central Bank of Chile CEFE, and UCLA, IO, Trade, Macro, and Applied pro-seminars for valuable comments. This study was developed within the scope of the research agenda conducted by the Central Bank of Chile (CBC) in economic and financial affairs of its competence. The CBC has access to anonymized information from various public and private entities, by virtue of collaboration agreements signed with these institutions. To secure the privacy of workers and firms, the CBC mandates that the development, extraction and publication of the results should not allow the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analysis was implemented by the authors and did not involve nor compromise the Servicios de Impuestos Internos de Chile. Corresponding author email: amartner@ucla.edu

1 Introduction

Aggregate total factor productivity (TFP) is the main source of income differences between countries. But what drives aggregate TFP growth? In the presence of distortions such as market power, taxes, or tariffs, aggregate TFP growth reflects not only technological advancements but also allocative efficiency, that is, how efficiently resources are allocated across agents. International trade has been argued for being an important driver of aggregate TFP improvements but whether this happens through technological advancements or allocative efficiency is still unclear. This is especially important for developing economies where distortions are ubiquitous and where international trade is claimed to be a fundamental force in driving aggregate TFP growth.

To this purpose, we present a theory for growth accounting in open economies with distortions. The theory extends Baqaee and Farhi (2020)'s theory of growth accounting with distortions to open economies. We focus on output distortions. These distortions generate a wedge between output price and marginal costs, a markup. This markup influences the allocative efficiency of the economy when doing growth accounting, as in Baqaee and Farhi (2020). While we keep a role for allocative efficiency in driving aggregate TFP growth through domestic wedges, we include wedges associated with export activity and wedges from imported intermediate inputs used in production. These wedges propagate downstream through the production network, affecting firms that consume intermediate inputs produced with imported goods- both directly or indirectly- which in turn affect their sales, either to other domestic firms, final consumers, or exporters.

Our main theoretical result shows that international trade influences growth accounting with distortions through three main channels.[1] First, through the production of goods that are exported. As with the production of goods for domestic consumption, if resources are reallocated to exporters with initially high markups, TFP will grow because those exporters were too small to begin with. This reallocation implies a reduction in labor and capital factor shares because resources are reallocated to firms that initially have relatively high markups. We call this the export channel of allocative efficiency.

Second, the above reallocation has different implications for changes in intermediate import shares. Intermediate inputs not produced domestically can be modeled as domestic factors, such as labor and capital because the supply of both is inelastic. However, the accounting for TFP growth decomposition is different because TFP, by definition, only

[1]These channels are absent for growth accounting in open economies when there are no distortions.

subtracts changes in domestic factors from changes in real GDP. Thus, one has to account for the feature that imported intermediate inputs used in firms that charge markups generate revenues that exceed their costs. We call this the import channel of allocative efficiency.

Finally, similar to above, given that imported intermediate inputs are modeled as factors but not discounted when measuring aggregate TFP, changes in the quantities of imported intermediate inputs must also be accounted for, scaled by the initial level of markups in firms that import both directly and indirectly. We call this channel the import bias.

We take this growth accounting framework to the data and measure the relevance of these channels by leveraging administrative tax information for all formal firms in Chile between 2005 and 2021. The growth accounting we derived implies measuring three objects: markups, cost-based Domar weights, and standard aggregate objects. We focus here on explaining the first two. We measure markups following Hall (1988) and De Loecker and Warzynski (2012). Under this method, markups are the ratio between the output elasticity of a variable input and the corresponding factor share. The main difference to the typical implementation of this method is that we directly control for output and input prices when estimating production functions. This allows us to infer quantity-based instead of revenue-based output elasticities and avoid a common critique from the literature (Bond et al., 2021).

To implement the derived growth accounting, we also need to measure cost-based Domar weights at the firm level. This measures how important is firms' output for final consumption both directly and indirectly through the entire production network. This is the theory-consistent measure for aggregating firm-level primitives changes such as TFP or markups. It is also the relevant measure of firm size for aggregation. The literature typically measures this object using industry input-output tables. Instead, we leverage firm-to-firm value-added tax data to measure all direct and indirect relationships between firms.

Using the above measures, we apply growth accounting in open economies with distortions to Chile. Aggregate TFP growth is positive during 2005-2011. After that, it stagnates until the end of the sample in 2021. The 2010 decade is a lost decade in terms of aggregate TFP growth. The main driver of aggregate TFP growth is allocative efficiency. It drives both the initial increase and the latter stagnation. In terms of cumulative growth between 2005 and 2021, allocative efficiency accounts for 83% of aggregate TFP growth.

To understand how allocative efficiency contributes to TFP growth, it is useful to decompose the evolution of average markups into whether firms change size, conditional on their initial markup (between component), or because markups change at the firm level, conditional on firm size (within component). We show that average markups in Chile increased between 2005 and 2021. However, in the first years of the sample, the increase in markups is driven mostly by the between component. This improves allocative efficiency because firms with initially relatively high markups that were originally too small are getting bigger. In the second half of the sample, the between component stagnates, and the within component becomes more important, which decreases allocative efficiency.

International trade accounts for 48% of the cumulative aggregate TFP growth between 2005 and 2021. The three channels described above account for the following shares. The export channel of allocative efficiency accounts for 23%, the import channel for 7%, and the import bias for 18%. That is, all channels are relevant in accounting for aggregate TFP growth.

Differences in these results across sectors inform the mechanisms behind the three mentioned channels. The role of international trade in allocative efficiency through the export and import channels is more relevant in sectors more exposed to international trade, such as agriculture, mining, and manufacturing. This result is not mechanic; non-tradable sectors such as specific services can also be indirectly affected by international trade through the use of imported intermediate inputs and selling their output to exporters.

Among these three sectors, the main channels driving the impact of international trade on allocative efficiency also vary. For agriculture, the export channel matters the most, whereas for mining and manufacturing, both the export and import channels matter. Finally, the import bias is relevant mostly for retail and wholesale. This sector is intensive in the import of intermediates and has high markups, but its import share has remained almost unchanged over time.

We compare our results to two benchmarks from the literature. First, we implement growth accounting with distortions but without international trade. This is what Baqaee and Farhi (2020) did. We find that aggregate TFP growth between 2005 and 2021 is 17%, whereas our benchmark with international trade gives 27%. The technological component of TFP growth remains almost unchanged. Thus, the main difference comes from accounting for the three international trade channels. The overall result that allocative efficiency accounts for most of TFP growth still holds. Second, we implement an industry version of the closed economy growth accounting with distortions. In this case, TFP growth is accounted for by the technological component instead of allocative efficiency. This implies that allocative efficiency matters within sectors and not between.

We relate to three strands of the literature. First, to the literature on growth accounting in the presence of distortions. Going back to Restuccia and Rogerson (2008), Hsieh and Klenow (2010) and Hsieh and Klenow (2009), it has been argued that distortions can be an important driver of aggregate TFP. This argument has been extended recently by Baqaee and Farhi (2020) to a more general framework with flexible production and preferences and general equilibrium. We extend this framework by incorporating international trade explicitly.

Second, we relate to the literature on how international trade in general, and imported intermediate inputs, in particular, affect aggregate TFP. The closest papers are Burstein and Cravino (2015), Blaum et al. (2018) and Kehoe and Ruhl (2008). To this literature we contribute by presenting a formula for growth accounting in open economies with distortions that is general and not subject to parametric assumptions other than constant returns to scale in preferences and technology. A common theme in the literature is that international trade contributes to aggregate productivity through factor reallocation between firms. We show that this logic is generalized in a world with distortions and that the reallocations through allocative efficiency are the main drivers of aggregate TFP. Also, relative to this literature, we highlight not only the role of imported intermediate inputs but also the role of exports in driving improvements in aggregate TFP and the issue about how GDP is measured, which affects the accounting of imported intermediate inputs. Our results highlight that these two additional channels are important for aggregate TFP growth.

Finally, we relate to the literature on the impact of trade in economies with distortions.[2] Feenstra et al. (2013) and Gopinath and Neiman (2014) show how, in the presence of specific distortions, changes in trade costs or in the terms of trade can result in changes in measured aggregate productivity. In terms of theory, we relate to Bai et al. (2023) and Baqaee and Farhi (2019). The closest paper is the latter, which presents a framework of trade in economies with distortions and derives several growth accounting decompositions. Rather than focusing on decomposing welfare growth as they do, we focus more on decomposing aggregate TFP growth and we expand the underlying forces behind how

[2]We also connect to the literature that highlights the impact of trade indirectly through production networks (Dhyne et al. (2023)). This literature mostly focuses on settings without distortions. We show how this mechanism interacts with distortions, and how both affect aggregate TFP growth.

international trade impacts aggregate TFP growth. Furthermore, the setting is also different because we treat the open economy as small instead of large as they do. We also discuss implementation issues when bringing these growth accounting formulae to the data, in particular by computing wedges at the firm level with quantity data and using firm-to-firm production network data to capture indirect linkages.

The remainder of the paper is organized as follows. Section 2 presents the theory for growth accounting. Section 3 describes the data. Section 4 presents the measurement and estimation strategy. Section 5 describes the results and Section 6 concludes.

2 Theory

To do growth accounting in open economies with distortions, we extend Baqaee and Farhi (2020) growth accounting framework to open economies in the spirit of Baqaee and Farhi (2019). Aggregate total factor productivity (TFP) growth depends on technological growth and allocative efficiency. While allocative efficiency is still affected by wedges within domestic production networks, we include wedges from imported intermediate inputs and wedges from exports. The imported intermediate input wedges might propagate downstream affecting firms that purchase intermediate inputs produced with imported goods- directly or indirectly- which in turn might affect their sales. These sales can be to other firms, domestic final consumers or exporters. Similarly, exporters sell their products by charging a markup which affects the size of these exporters and how much labor and capital they use. We provide results that decompose and interpret the drivers of aggregate productivity changes, in particular the role of international trade in shaping the evolution of aggregate productivity.

Define N as the set of firms. We define the production function separately for domestic and export goods within a firm. We assume constant returns to scale (CRS) in the production function, so separating the production function into domestic and export goods is without loss of generality. Thus, we divide the firm into two fictitious firms, one producing domestic goods and the other exporting goods, where D is the set of firms that supply goods domestically and X is the set of firms that export:

$$q_i = A_i F_i \left(\left\{ q_{ij} \right\}_{j \in D}, L_{L,i}, L_{K,i}, L_{IM,i} \right),$$

where q_i is the total output of firm i, A_i is Hicks-neutral productivity, q_{ij} are the domestic intermediate goods input from other $j \in D$ firms.[3] Labor (L_L), Capital (L_K), and imported inputs (L_{IM}) are this economy's primary production factors.

Firms minimize costs given input prices and sell their products by charging a markup (μ) over marginal cost:

$$p_i = \mu_i mc_i.$$

There is a representative household in the domestic economy with the following homothetic utility function

$$\mathcal{W} = \mathcal{W}\left(\{y_i\}_{i \in D}\right),$$

while export demand is given exogenously by y_i if $i \in X$. The budget constraint is expressed as:

$$\sum_{i \in D} p_i y_i = \sum_{f \in \{L,K\}} w_f L_f + \sum_{i \in D+X} (1 - 1/\mu_i)\, p_i q_i$$

The left-hand-side represents expenditures of the household. The right-hand-side represents income of the household. Income can be decomposed into factor income, which comes from labor and capital, and non-factor income, which comes from profit ownership. We treat imports as a factor because they are produced outside of the domestic economy. Thus, the factor income associated with imports does not appear in household budget constraints as it is attributed to foreign households.[4] Note that this budget constraint implies that households cannot import final goods directly. All imports are channeled through intermediates. This assumption comes from a feature of the data: final goods imports are also channeled through intermediaries (either retail or wholesale). Thus, this assumption is without much loss relative to the data, because the model will feature retail and wholesale intermediaries. Finally, the foreign demand and import price are exogenous and GDP is the numeraire.

Market clearing conditions are the following. For goods $i \in D$,

$$q_i = y_i + \sum_{j \in D} q_{ji}$$

and for $i \in X$, $q_i = y_i$. For factors, we have the following market clearing conditions:

[3] By definition, exporters do not sell intermediate goods domestically.

[4] We assume that profits are accrued to the supplier of the good, and therefore profits associated with imported goods are income to the foreign household. This affects how international trade-related wedges impact the domestic economy. Nevertheless, this assumption is standard in the literature (Atkin and Donaldson, 2022).

$$\sum_{i \in D+X} L_{L,i} = L_L, \quad \sum_{i \in D+X} L_{K,i} = L_K, \quad \sum_{i \in D+X} L_{IM,i} = L_{IM}.$$

General Equilibrium

Given productivity A_i, markup μ_i, exogenous foreign demand, and exogenous import prices, the general equilibrium is the set of prices p_i, intermediate input choices q_{ij}, factor input choices $\{L_{L,i}, L_{K,i}, L_{IM,i}\}$, output q_i, and consumption choices y_i, such that: (i) the price of each good is equal to its markup multiplied by its marginal cost; (ii) households maximize utility under budget constraints, given prices; and (iii) markets clear for all goods and factors.

National Accounts

Using the expenditure approach, nominal GDP is the sum of domestic and foreign final demand minus imports.

$$GDP = \sum_{i \in D+X} p_i y_i - w_{IM} L_{IM}.$$

GDP shares for each final output are described by the following vector:

$$b_i = \begin{cases} \frac{p_i y_i}{GDP} & \text{if } i \in D+X \\ -\frac{w_{IM} L_{IM}}{GDP} & \text{if } i \in IM \\ 0 & \text{otherwise} \end{cases}$$

Given the definition of GDP, the GDP deflator is defined as a chained index as follows:

$$d \log P = \sum_{i \in D+X} \frac{p_i y_i}{GDP} d \log p_i - \frac{w_{IM} L_{IM}}{GDP} d \log w_{IM},$$

which can be expressed in vector form using the GDP share b_i as,

$$d \log P = b' d \log p,$$

where $d \log p$ is a vector of $D + X + F$ prices, with D, X, and F representing the sets of firms, exporters, and production factors, respectively.[5] Then, real GDP growth is computed by chaining absolute indices:

$$d\log Y = d\log GDP - d\log P.$$

Finally, we define the aggregate factor shares and import shares as

$$\Lambda_L \equiv \frac{w_L L_L}{GDP}, \quad \Lambda_K \equiv \frac{w_K L_K}{GDP}, \quad \Lambda_{IM} \equiv \frac{w_{IM} L_{IM}}{GDP}.$$

Factor shares used for domestic production and exports are defined as follows:

$$\Lambda_L^D \equiv \frac{\sum_{i\in D} w_L L_{L,i}}{GDP}, \quad \Lambda_K^D \equiv \frac{\sum_{i\in D} w_K L_{K,i}}{GDP}, \quad \Lambda_L^X \equiv \frac{\sum_{i\in X} w_L L_{L,i}}{GDP}, \quad \Lambda_K^X \equiv \frac{\sum_{i\in X} w_K L_{K,i}}{GDP}.$$

Input-Output Objects

The input-output (IO) matrix groups all firm-to-firm transactions and factor expenditures in a matrix of dimensions $(D + X + F) \times (D + X + F)$. We define the cost-based IO matrix $\tilde{\Omega}$, which describes the share of expenditures in firms' total costs. By Shepherd's Lemma, the expenditure share of production costs for firm i from an origin j is

$$\tilde{\Omega}_{ij} = \frac{\text{Value of input j used by firm i}}{\text{Firm i total cost}} = \frac{p_j q_{ij}}{\sum_{j\in D+F} p_j q_{ij}}.$$

The cost-based Leontief inverse matrix $\tilde{\Psi}$ accounts for both direct and indirect cost exposures of every firm through the economy's production network. Each element of $\tilde{\Psi}$ measures the weighted sums of all paths (steps) of all length size from producer j to producer i.

$$\tilde{\Psi} \equiv (I - \tilde{\Omega})^{-1} = I + \tilde{\Omega} + \tilde{\Omega}^2 + \dots$$

We define cost-based Domar weights as $\tilde{\lambda}$ for firms and $\tilde{\Lambda}$ for factors,[6] as the interaction of firms and factors GDP exposure (measured by b) with their relevance throughout

[5]In our case, since we defined the factors to be capital, labor and imports, we have $F = 3$.

[6]Denote $\tilde{\Lambda}_f$ if $f \in \{\text{L,K,IM}\}$.

the production network (measured by $\tilde{\Psi}$,

$$\tilde{\lambda}' \equiv b'\tilde{\Psi}.$$

Cost-based Domar weights capture the impact of firm-level cost shocks (driven by changes in productivity or markups) on GDP.

Growth Accounting

Following Baqaee and Farhi (2020) an allocation matrix $\mathcal{X}$ captures admissible allocation of resources, where each of its elements $\mathcal{X}_{ij} = q_{ij}/y_j$ is firm j output share used in production by firm i. All feasible allocations are defined by an allocation matrix $\mathcal{X}$, a vector of productivity A, a vector of markup μ, and a vector of factor supplies, F, which consists of L, K, and IM. In particular, the equilibrium allocation yields an allocation matrix $\mathcal{X}(A, F, \mu)$, which in turn generates an output level of $\mathcal{Y}(A, \mathcal{X}(A, F, \mu))$.

A productivity shock ($\mathrm{d}\log A$) and a markup shock ($\mathrm{d}\log\mu$) effect in real GDP can be decomposed into a pure change in technology ($\mathrm{d}\log A$) for a given fixed allocation matrix $\mathcal{X}$ and the change in the distribution of resources allocation matrix ($\mathrm{d}\mathcal{X}$) holding technology constant. In vector notation:

$$\mathrm{d}\log Y = \underbrace{\frac{\partial \log \mathcal{Y}}{\partial \log A}\mathrm{d}\log A}_{\Delta \text{ Technology}} + \underbrace{\frac{\partial \log \mathcal{Y}}{\partial \mathcal{X}}\mathrm{d}\log \mathcal{X}}_{\Delta \text{ Allocative Efficiency}}$$

Given this, Proposition 1 characterizes growth accounting for open economies with distortions.

Proposition 1. *The change in TFP in response to productivity shocks, factor supply shocks, and shocks to wedges can be summarized, to a first-order, as:*

$$\underbrace{\Delta \log Y_t - \sum_{f\in\{L,K\}} \tilde{\Lambda}_{f,t-1}\Delta \log L_{f,t}}_{\Delta\ \textit{Agreggate TFP}} = \underbrace{\sum_{i\in D+X} \tilde{\lambda}_{i,t-1}\, d\log A_i}_{\Delta\ \textit{Technology}}$$

$$
- \underbrace{\sum_{f \in \{L,K\}} \tilde{\Lambda}_{f,t-1} \frac{d\Lambda_f^D}{\Lambda_f} - \sum_{i \in D} \tilde{\lambda}_{i,t-1}\, d\log \mu_i}_{\Delta \text{ Domestic Allocative Efficiency}}
$$

$$
- \underbrace{\sum_{f \in \{L,K\}} \tilde{\Lambda}_{f,t-1} \frac{d\Lambda_f^X}{\Lambda_f} - \sum_{i \in X} \tilde{\lambda}_{i,t-1}\, d\log \mu_i}_{\Delta \text{ Export Allocative Efficiency}} - \underbrace{\left(\tilde{\Lambda}_{IM,t-1} - \Lambda_{IM,t-1}\right) d\log \Lambda_{IM,t}}_{\Delta \text{ Import Allocative Efficiency}}
$$

$$
+ \underbrace{\left(\tilde{\Lambda}_{IM,t-1} - \Lambda_{IM,t-1}\right) d\log L_{IM}}_{\Delta \text{ Import Bias}}
$$

The proof can be found in Appendix A.[7] The change in aggregate TFP can be decomposed into five terms. First, by technological changes driven by A, which is measured as a residual. Second, by allocative efficiency associated with domestic production. Third and fourth, by allocative efficiency associated with exports and imports, respectively. Finally, by an import bias term. We explain each of these terms in turn.

The first term, technology, is the same term of technology as in Baqaee and Farhi (2020). It represents how Hicks-neutral productivity shifter drives aggregate TFP, weighted by the cost-based Domar weight.

The second term is domestic allocative efficiency. The first object is the contribution of domestic production to the change in factor share and has the following intuition. To improve allocative efficiency, it is necessary to reallocate resources to parts of the economy that are underproducing in the initial equilibrium due to high markups. If this reallocation results in a larger share of activity of initially high markup firms, the factor share will decline. However, the change in factor share is not only driven by reallocation but also by changes in markups. To measure pure reallocation changes, the change in factor share due to markup changes must be discounted, which is captured in the second object. This same intuition applies to Baqaee and Farhi (2020).

The third term is allocative efficiency driven by exports. The interpretation is the same as for domestic production, but in the context of export activity. That is, the contribution of changes in factor shares and markup adjustments due to export activity. We call this the export channel of allocative efficiency.

[7] This proposition is based on Baqaee and Farhi (2019) but we added a different proof. The main difference is we treat imported goods as a factor and then subsequently remove them according to the GDP definition.

The fourth term relates to the treatment of imports in GDP. Similar to the reallocation argument done above, if resources are reallocated to firms that have initially high markups, the intermediate import share will decline. Since markups due to imports are accrued to foreign households, markup changes discounting is not needed. Finally, the magnitude of the impact of changes in intermediate import shares depends on how relevant are markups in the initial equilibrium, which is proxied by $\tilde{\Lambda}_{IM,t-1} - \Lambda_{IM,t-1}$. This captures the fact that in an economy where imports are used as intermediate inputs and firms impose markups, the revenues generated by imports exceed their costs. In a world without distortions, $\tilde{\Lambda}_{IM,t-1} = \Lambda_{IM,t-1}$, and thus there is no impact from reallocation of imports. We call this term the import channel of allocative efficiency.

The last term, the import bias, comes from accounting and how aggregate TFP is defined. By definition, aggregate TFP accounts for value-added after the quantities of labor and capital are subtracted. Thus, although imports are a factor in this economy, they are not subtracted to measure aggregate TFP. Furthermore, in national accounting imports are subtracted using the revenue-based measure Λ_{IM} whereas in an economy with distortions they should be subtracted using the cost-based measure $\tilde{\Lambda}_{IM}$.

Note that international trade can potentially also influence cost-based Domar weights. This is because the cost-based Leontief inverse is affected by imports and exports. This influence ultimately depends on how export and import activity is measured and allocated. On the export side, this depends on how we split the firm into the production of domestic and export goods. On the import side, it depends on how imported intermediate inputs affect shares of the cost-based IO matrix, $\tilde{\Omega}$. We will return to this in the context of the implementation details and the results in Section 5.

3 Data

We use data from five different administrative sources of the Chilean IRS (Servicio de Impuestos Internos, SII). One of the advantages of SII data is that firms and workers have a unique tax identifier, which allows the merging of individuals and firms across data sets.

The first source used is the value-added tax form (F29). This form includes information about total sales, total materials expenditures, total imports, total exports, investment and main industry of the firm. This industry classification is at the 6-digit ISIC (rev. 4) level (more than 600 sectors). This form covers all formal firms in the economy.

Second, we use the tax form DJ1887 which has information about employer-employee relationships. Specifically, firms report all their payments to individual workers: the sum of taxable wages, overtime, bonuses, and any other labor earnings for each fiscal year. Since all legal firms must report to the SII, the data covers the total labor force with a formal labor contract, representing roughly 65% of employment in Chile (Central Bank of Chile, 2018). This form allows us to measure total employment and total wage bill of the firm.

Third, we use the income tax form (F22) which gathers yearly information on firms' balance sheet. This form covers all formal firms in the economy. From this form we use data on fixed assets to measure the capital stock of the firm with perpetual inventory methods. As initial condition, we use the first value of fixed assets reported by the firm and then investment from the tax form F29 to update the capital stock. The real rental rate of capital is built using publicly available data. We use the 10-year government bond interest rate minus expected inflation plus the external financing premium. Also, we use the capital depreciation rate from the LA-Klems database.

Fourth, we use data from buying and selling books (forms 3327-3328 and form 3323) for 2005-2014. This data provides information on transactions between firms.

Fifth, we use data from electronic tax documents that provide information on each product, including its price and quantity, traded domestically or internationally with at least one Chilean firm as a buyer or supplier from 2014 onwards. We use it to complement the buying and selling books to build the production network for the whole 2005-2021 period.

The data is anonymized to ensure confidentiality regarding the firm's and workers' identities. A set of filters is applied over the raw data to obtain the final data set for the empirical analysis. First, for the complete data set, a firm is defined as active in a particular year if it has a tax ID, positive sales, materials, wage bill, and capital. We assume this as all dimensions are necessary for estimating production functions. Second, firms that hire two or less employees or have capital valued below US$20 a year are dropped. Third, all variables are winzorized at 1% and 99% levels to avoid measurement error due to outliers. These filters generate an economy-wide yearly firm panel for 2005-2021.

4 Measurement and Estimation

As established in Section 2, to do growth accounting in open economies with distortions one needs to measure, three objects: (1) markups μ_i, (2) cost-based Domar weights $\tilde{\lambda}_i$ and (3) aggregates such as value-added, factor changes and total import changes. We discuss each of these in turn.

4.1 Markups

We estimate markups following the production approach presented by Hall (1988) and popularized by De Loecker and Warzynski (2012) which exploits the first-order condition of firms' cost minimization problem. This approach implies that markups can be expressed as the ratio between output elasticities and input shares of a variable input. We use materials as a variable input since this is typically the more flexible input (at least relatively more than labor and capital). Since we use a standard estimation strategy from the literature, we relegate the estimation details of markups to Appendix B. We only discuss here some implementation details regarding production function estimation.

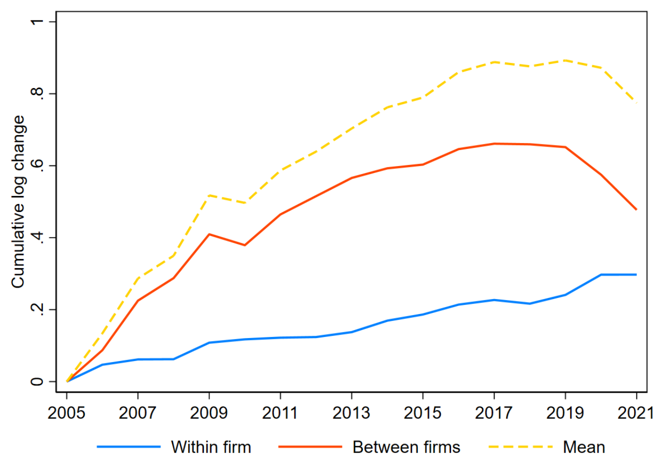
One of the ingredients necessary for recovering markups are output elasticities of materials. For this, we need to specify the technology and estimate production functions. We assume a Cobb-Douglas production function with time-invariant output elasticities. We estimate the production function separately for each 6-digit sector (which represents 626 sectors) that has at least 100 observations during our sample to recover output elasticities. Following Foster et al. (2022), we allow output elasticities to vary as much as possible by using the most disaggregated sector classification available in Chile. The firm-year observations belonging to sectors with more than 100 observations represent 97% of the sample. For the remaining sample for which we do not have enough observations, we estimate sectoral output elasticities at a higher level of sectoral aggregation: 160 sectors. We leverage the transaction-level price data to estimate the production function using real, rather than nominal, inputs and outputs.

Figure 1 presents the evolution of markups. We show the sales-weighted harmonic mean. This is the correct way to aggregate markups to match the aggregate profit share. It is also what the literature has shown and so it is useful to benchmark our results (Baqaee and Farhi, 2020). From 2005 to 2019 markups increased on average by 81%.[8] To under-

[8]In Appendix B, we show other moments of the evolution of markups. We find that simple average means and other weighted means also increased during these years.

stand where these changes come from, Figure 1 also presents a decomposition of markup changes into changes within versus between firms.[9] The within component represents changes of the markup for each firm, while keeping firm size constant. The between component is the residual so it accounts for compositional changes (even without changing firm-level markups, changes in firm size might lead to aggregate changes in markups) and also entry and exit. Figure 1 shows that the predominant factor leading the growth in markups is the between component. This implies that markups have increased because firms with relatively high markups have become larger and not because firms are increasing their markups on average.[10] This result has relevant implications for growth accounting because it implies that changes in allocative efficiency have a positive contribution to TFP growth.

Figure 1: Evolution of markups and within-between firm decomposition



4.2 Cost-Based Domar Weights

The second object necessary to do growth accounting in open economies with distortions is cost-based Domar weights,

$$\tilde{\lambda}_i \equiv b'\tilde{\Psi} = b'(I + \tilde{\Omega} + \tilde{\Omega}^2 + \ldots). \qquad (1)$$

[9] $$\underbrace{\Delta \log \frac{1}{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}}}}_{\text{Harmonic Sales-Weighted Average}} = \underbrace{\frac{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}} \Delta \log \mu_{it}}{\sum_i \hat{\lambda}_{it} \frac{1}{\mu_{it}}}}_{\text{Within}} + \underbrace{\text{Residual}}_{\text{Between}}$$

[10] We confirm that this is not driven by entry and exit by implementing the decomposition from De Loecker et al. (2020).

For this, we need to measure final expenditure shares b and the input-output matrix $\tilde{\Omega}$. We can measure these objects directly from the data. Final expenditure shares b, a vector of dimension $(D+X+F)\times 1$, where D is the number of firms that sell domestically, X is the number of firms that export, F is the number of factors, is measured relative to GDP. The first D entries are measured by taking the residual between firms' total sales (excluding exports) and firms' intermediate sales to other firms (which we measure from the firm-to-firm data). This is the theory-consistent measure for final expenditures. For the next X entries, we measure them directly using firms exports. The final F entries are zero because the household does not buy factors directly.

We measure the input-output matrix $\tilde{\Omega}$ at the firm-level using the firm-to-firm datasets and factor expenditures.[11] The $(D+X+F)\times(D+X+F)$ $\tilde{\Omega}$ matrix is composed of different blocks:

$$\tilde{\Omega} = \begin{bmatrix} \tilde{\Omega}_{DD} & \tilde{\Omega}_{DX} & \tilde{\Omega}_{DF} \\ \tilde{\Omega}_{XD} & \tilde{\Omega}_{XX} & \tilde{\Omega}_{XF} \\ \tilde{\Omega}_{FD} & \tilde{\Omega}_{FX} & \tilde{\Omega}_{FF} \end{bmatrix}$$

Since factors do not require inputs, the last row of matrices is zero, $\tilde{\Omega}_{Fj} = 0$ for all $j = \{D, X, F\}$. The fact that exports are sold only internationally implies that $\tilde{\Omega}_{DX} = 0$ and $\tilde{\Omega}_{XX} = 0$. The denominator of the remaining matrices is firms' total costs which we measure as the sum of expenditures on intermediate inputs, the wage bill and the capital level multiplied by the user cost of capital. The numerator of $\tilde{\Omega}_{DD}$ and $\tilde{\Omega}_{XD}$ is measured using the domestic firm-to-firm matrix and correspond to the trade flow between firms. The numerator of $\tilde{\Omega}_{DF}$ and $\tilde{\Omega}_{XF}$ correspond to factor expenditures used in producing domestic goods and exports.[12] We measure three factors: labor, capital and imported intermediate inputs ($F = 3$).

One important feature behind $\tilde{\lambda}_i$ is the role played by international trade. Is possible to decompose $\tilde{\Psi}$ into block matrices similar to how we did with $\tilde{\Omega}$. Since imports are a factor in this economy, international trade plays a role on $\tilde{\Psi}_{DF}$ and $\tilde{\Psi}_{XF}$. Furthermore, these matrices can be decomposed into different matrix blocks that represent the role played by each factor. For instance, for the role that factors play in the production of

[11] Appendix C shows the robustness of our results to using a standard industry-level input-output table.

[12] For firms that sell domestically and export, we allocate intermediate inputs and factors to exporting in proportion to export share in total sales of those firms. Among exporters, the majority of firms also sell domestically.

goods sold domestically, we have,

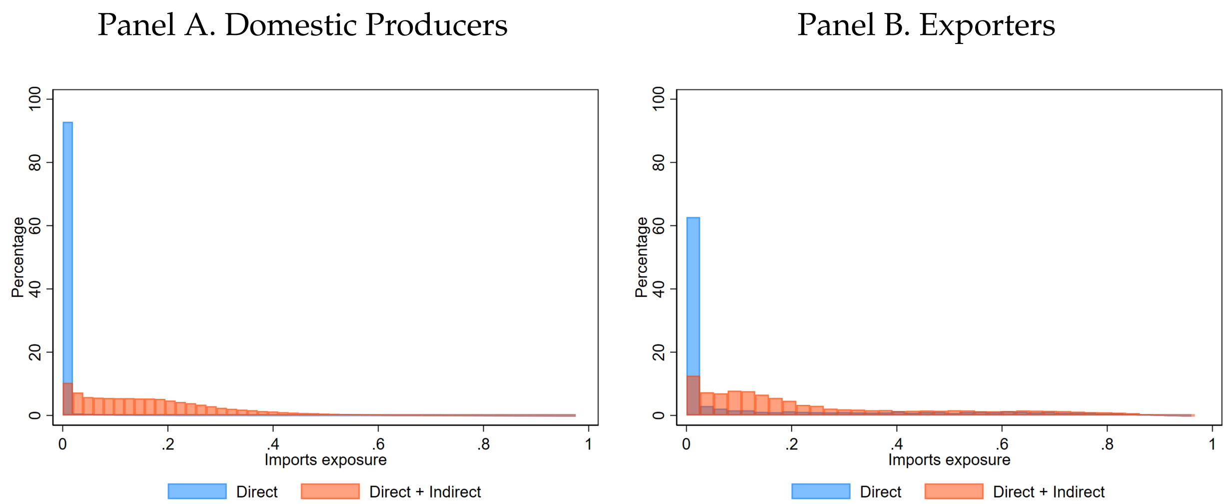
$$\tilde{\Psi}_{DF} = \begin{bmatrix} \tilde{\Psi}_{DL} & \tilde{\Psi}_{DK} & \tilde{\Psi}_{DM} \end{bmatrix}.$$

The entries of $\tilde{\Psi}_{DM}$ measure the relevance that imports have in producing goods sold domestically, both directly and indirectly. A similar argument holds for exports through $\tilde{\Psi}_{XM}$. As a benchmark, we compare those matrices relative to the direct role that imports have in importers' costs, measured by $\tilde{\Omega}_{DM}$ and $\tilde{\Omega}_{XM}$, for both domestic producers and exporters, respectively.

Figure 2 shows patterns behind $\tilde{\Psi}_{DM}$ and $\tilde{\Psi}_{XM}$, and $\tilde{\Omega}_{DM}$ and $\tilde{\Omega}_{XM}$. Panel A shows the distribution of the exposure to imports of domestic producers, both directly ($\tilde{\Omega}_{DM}$) and indirectly through the production network ($\tilde{\Psi}_{DM}$). Direct exposure is concentrated in a small share of firms (11%), but the indirect exposure is distributed across the economy, i.e., 1% of firms have zero indirect exposure to imports. This shows how important it is to consider indirect exposure when measuring the impact of imports on domestic producers.

Panel B of Figure 2 shows the distribution of the exposure to imports of exporters, both directly ($\tilde{\Omega}_{XM}$) and indirectly through the production network ($\tilde{\Psi}_{XM}$). Here, the share of firms directly exposed to imports is relatively larger (38% of exporters). This shows that exporters rely relatively more on imports as they engage more intensively with international trade than domestic producers. Although not all exporters are directly exposed to imports, all of them are exposed indirectly, highlighting that even for firms that engage in international trade, the indirect exposure to imports is relevant.

Figure 2: Direct and Indirect Exposure to Imported Intermediate Inputs



Finally, we discuss how cost-based Domar weights are when ignoring international trade. We implement a particular strategy of what "ignoring international trade" means. The ultimate result depends on this strategy. We assume that, when facing tax data, exports are included in total sales of firms and imports are included in intermediate input expenses. Thus, we measure cost-based Domar weight using those total sales and total expenses, thereby including export as a revenue and imports as a cost, but not separating them from other sources of revenue and costs as we do in this paper. This also helps in keeping aggregates the same when comparing the two approaches. When comparing our benchmark cost-based Domar weight with the one that ignores international trade, we sum the domestic and export cost-based Domar weight for firms that perform both activities. We find that both measures are the same up to rounding errors coming from matrix inversions. This happens for two reasons. First, when we split firms into domestic production and exporting, we allocate factors and input proportionally to the export share of revenues. This implies that the markup is the same for both entities and that, after summing them, they are also the same in terms of total sales. Second, when we allocate imports to domestic material expenses in measuring the cost-based Domar weight that ignores international trade, we keep the same shares of the input-output matrix. These two reasons imply both that the cost-based Leontief inverse and the final expenditure shares are the same, and therefore also the cost-based Domar weight. Although implementing a different strategy for ignoring international trade could deliver differences in the cost-based Domar weights, we argue that this is not a main feature when highlighting the role of international trade for aggregate TFP growth.

4.3 Aggregate Objects

Besides markups and cost-based Domar weights, for implementing growth accounting presented in Proposition 1, we need to measure aggregate objects. In particular, Y, L_L, L_K, L_{IM}, Λ_M, which denote aggregate value added, employment, capital, imports and import share, respectively. We measure Y, L_L, L_K and L_{IM} as the sum of firms' value added, employment, capital and imports, respectively, across all firms in the economy. Imports share of GDP, Λ_M, is measured as total import flows divided by GDP.

5 Results

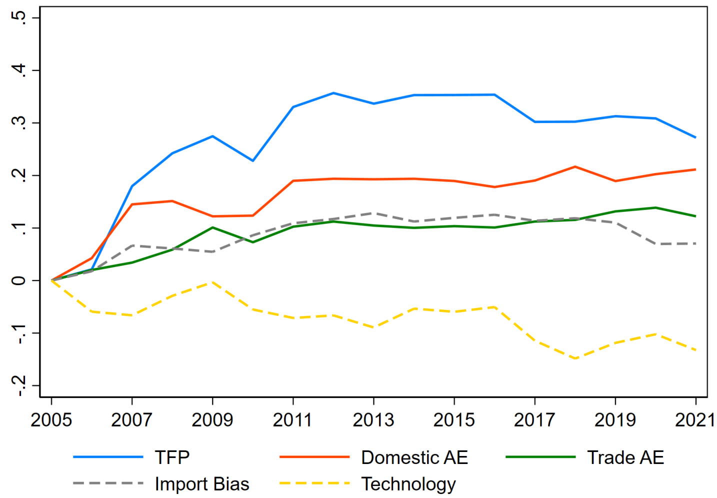
Figure 8 displays the growth accounting for open economies with distortions presented in Proposition 1. Aggregate TFP, measured by the distortion-adjusted Solow residual exhibited strong growth between 2005 and 2011. After that, TFP has been stagnated. The TFP level in 2021 is actually lower a decade later in 2011. The 2010s is a lost decade for productivity growth in Chile.[13]

Aggregate TFP growth is primarily driven by resource reallocation, measured through allocative efficiency. By combining the domestic and international trade aspects of allocative efficiency, one can account for 83% of the cumulative growth of aggregate TFP between 2005 and 2021. The technological component is continuously declining over the sample period.

As mentioned in Proposition 1, international trade can impact aggregate TFP growth through three channels: the export channel of allocative efficiency, the import channel of allocative efficiency, and the import bias. The first two channels, which combined represent the role of trade through allocative efficiency, account for 30% of the cumulative growth of aggregate TFP between 2005 and 2021. The pattern relative to domestic allocative efficiency is also similar. Both measures of allocative efficiency grew stronger between 2005 and 2011, compared to between 2012 and 2021. Finally, the import bias represents 18% of the cumulative growth of aggregate TFP between 2005 and 2021. Overall, this implies that international trade accounts for 48% of the cumulative growth of aggregate TFP between 2005 and 2021.

[13]These aggregate results are consistent with more standard measures of aggregate TFP growth that ignore both distortions and international trade (Central Bank of Chile, 2021).

Figure 3: Growth Accounting in Open Economies with Distortions
Percentage growth relative to 2005 levels



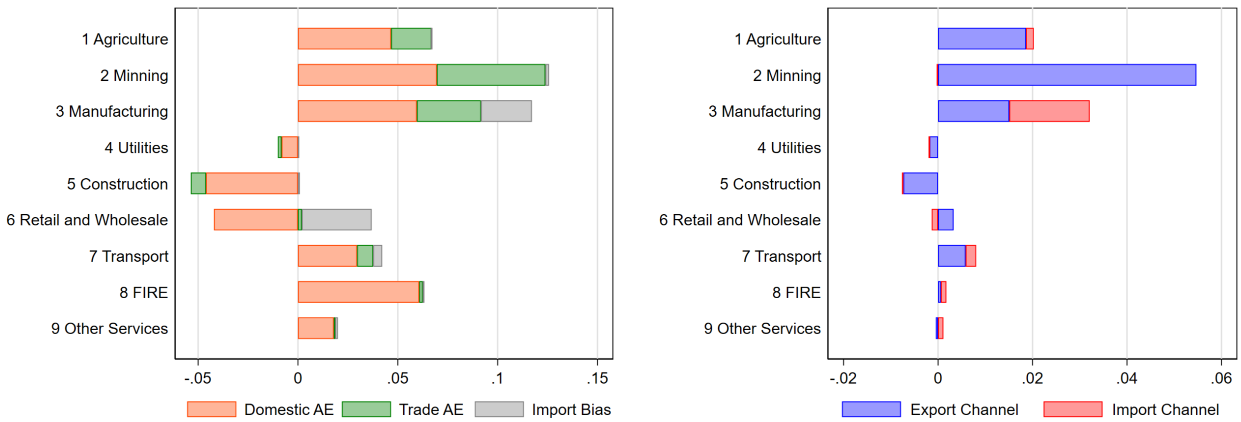
Notes: AE stands for Allocative Efficiency

We explore the role of sectoral differences in growth accounting to better understand the mechanisms behind our decomposition. Figure 4 presents the role of the different channels behind growth accounting for the cumulative growth of aggregate TFP between 2005 and 2021. We find that allocative efficiency matters the most in sectors that are relatively exposed to international trade, such as agriculture, mining and manufacturing. It can also matter for non-tradable sectors such as construction and transports, but relatively less. The import bias, on the other hand, matters for manufacturing and also for a non-tradable sector: retail and wholesale. The imports bias actually compensates the fact that domestic allocative efficiency goes down for this sector. Imports are high for retail and wholesale, and this is also a sector that has high markup. This result highlights that accounting for the fact that aggregate TFP does not discount imports properly is important for this sector.

Panel B of Figure 4 further opens the role of international trade on allocative efficiency on the export and import channel. The export channel is the most relevant one across sectors. The import channel is relevant for manufacturing. This the typical channel that the literature emphasizes: the role of imported intermediate inputs on manufacturing. We show here that this is a fraction of the overall role of trade in shaping aggregate TFP.

Figure 4: The Role of International Trade for Aggregate TFP Growth: Across Sectors

Panel A. Three Channels Panel B. Export and Import Channel of AE



Notes: AE stands for Allocative Efficiency

6 Conclusion

TBD

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Appendix

A Proof of proposition 1

Proof. We start from the price equation; for all $i \in D + X$

$$d \log p_i = -d \log A_i + d \log \mu_i + \sum_{j \in D} \tilde{\Omega}_{ij} d \log p_{ij} + \sum_{f \in L,K,IM} \tilde{\Omega}_{if} d \log w_f,$$

In matrix notation, we have

$$\begin{aligned} d \log p &= (I - \tilde{\Omega}^{(D+X)\times(D+X)})^{-1} \left[-d \log A + d \log \mu + \tilde{\Omega}^{(D+X)\times F} d \log w_f \right] \\ &= -(I - \tilde{\Omega}^{(D+X)\times(D+X)})^{-1} [d \log A - d \log \mu] + (I - \tilde{\Omega}^{(D+X)\times(D+X)})^{-1} \tilde{\Omega}^{(D+X)\times F} d \log w_f \end{aligned}$$

where $\tilde{\Omega}^{(D+X)\times(D+X)}$ is the square matrix extracted for the first $(D + X) \times (D + X)$ of the cost-based IO matrix, $\tilde{\Omega}$. From the property of inverse matrix , $(I - \tilde{\Omega}^{(D+X)\times(D+X)})^{-1}$ is equal to the first $(D + X)$ matrix extracted from cost-based Leontief inverse matrix, $\tilde{\Psi}$. Therefore, we could express

$$\begin{aligned} d \log p_i &= -\sum_j \tilde{\Psi}_{ij} [d \log A_j - d \log \mu_j] + \sum_{f \in L,K,IM} \tilde{\Psi}_{if} d \log w_f, \\ &= -\sum_j \tilde{\Psi}_{ij} [d \log A_j - d \log \mu_j] + \sum_{f \in L,K,IM} \tilde{\Psi}_{if} \left(d \log \Lambda_f - d \log L_f \right) \end{aligned}$$

using the definition of GDP deflator, we know

$$d \log P = \sum_{i \in D+X} \frac{p_i y_i}{GDP} d \log p_i - \frac{w_{IM} L_{IM}}{GDP} d \log w_{IM}$$

Therefore,

$$\begin{aligned} d \log P &= b' d \log p \\ &= \sum_{i \in D+X} \tilde{\lambda}_i \left(d \log A - d \log \mu \right) + \sum_{f \in L,K} \tilde{\Lambda}_f w_f - \Lambda^{IM} d \log w_{IM}, \\ &= \sum_{i \in D+X} \tilde{\lambda}_i \left(d \log A - d \log \mu \right) + \sum_{f \in L,K} \tilde{\Lambda}_f \left(d \log \Lambda_f - d \log L_f \right) - \Lambda^{IM} \left(d \log \Lambda_{IM} - d \log L_{IM} \right) \end{aligned}$$

Since we know $d\log Y = d\log GDP - d\log P$ and nominal GDP is numeraire,

$$\begin{aligned}
d\log Y &= d\log GDP - d\log P,\\
&= -\left(-\sum_{i\in D+X}\tilde{\lambda}_i\left(d\log A - d\log\mu\right) + \sum_{f\in L,K}\tilde{\Lambda}_f\left(d\log\Lambda_f - d\log L_f\right) - \Lambda^{IM}\left(d\log\Lambda_{IM} - d\log L_{IM}\right)\right),\\
&= -\sum_{i\in D+X}\tilde{\lambda}_i d\log A + \sum_{i\in D+X}\tilde{\lambda}_i d\log\mu + \sum_{f\in L,K}\tilde{\Lambda}_f\left(d\log\Lambda_f - d\log L_f\right) - \Lambda^{IM}\left(d\log\Lambda_{IM} - d\log L_{IM}\right)
\end{aligned}$$

Following to Baqaee and Farhi (2020), define distortion-adjusted TFP as

$$d\log TFP = d\log Y - \sum_{f\in L,K}\tilde{\Lambda}_f d\log L_f$$

Therefore, we have

$$\begin{aligned}
d\log TFP &= d\log Y - \sum_{f\in L,K}\tilde{\Lambda}_f d\log L_f,\\
&= -\sum_{i\in D+X}\tilde{\lambda}_i d\log A + \sum_{i\in D+X}\tilde{\lambda}_i d\log\mu - \sum_{f\in L,K}\tilde{\Lambda}_f d\log\Lambda_f - \left(\tilde{\Lambda}_{IM} - \Lambda_{IM}\right)\left(d\log\Lambda_{IM}\right)\\
&+ \left(\tilde{\Lambda}_{IM} - \Lambda_{IM}\right) d\log L_{IM}
\end{aligned}$$

Notice that at first order, we know

$$\sum_{f\in\{L,K\}}\tilde{\Lambda}_{t-1} d\log\Lambda_f = \sum_{f\in\{L,K\}}\tilde{\Lambda}_{t-1} d\log\frac{d\Lambda_f^D}{\Lambda_f} + \sum_{f\in\{L,K\}}\tilde{\Lambda}_{t-1} d\log\frac{d\Lambda_f^X}{\Lambda_f}$$

Substitute this equation into the TFP equation and rearrange to obtain the desired result.

□

B Markup estimation strategy and results

Following De Loecker and Warzynski (2012), from the cost minimization problem faced by firm i, we can define the markup charged by firm i in period t (μ_i) as the price over the marginal cost, or equivalently as the variable input share (s_{it}^V) over the output elasticity of a variable input (θ_{it}^V). While s_{it}^V is observed, estimating the θ_{it}^V represents this approach's main challenge. Importantly, this methodology does not need any assumptions regarding the demand structure or competitive dynamics.

We use an output-based Cobb-Douglas production function with three factors: capital (K), Labor (L), and Materials (M) to recover material-output elasticities where lowercase variables denote natural logarithms:

$$q_{it} = A_{it} + \beta_l \, l_{it} + \beta_k \, k_{it} + \beta_m + \epsilon_{it}$$

To ensure parameter identification, we draw upon Ackerberg et al. (2015). The sequence of decisions required for identification proceeds as follows: Capital is a state variable determined at period $t-1$. Labor can be selected between $t-1$ and t, but always after the capital decision and before the materials decision. While it is acknowledged that demand-side shocks can potentially impact markup measures (Doraszelski and Jaumandreu (2021)), addressing these concerns goes beyond the scope of this work.

To recover price variation-free variables for output and materials, we construct firm-level price indexes using standard Tornqvist indices. This method to build price indices is widely recognized for estimating aggregate production functions at the firm or plant level when price data is accessible (Dhyne et al. (2022) and De Roux et al. (2021)). This allows us to infer quantity-based instead of revenue-based output elasticities and avoid a common critique from the literature ((Bond et al., 2021)).

We compute firm-specific annual weighted average prices (P_{igt}) for each product (g) sold by firm i during year t. Subsequently, we construct firm-specific price indices (ΔP_{it}) for products observed in consecutive years using the product-level weighted average price and the share of the product present in both year $t-1$ and year t:

$$\Delta \log P_{it} = \sum_{g} \frac{s_{igt} + s_{igt-1}}{2} \, \Delta \log(P_{igt})$$

Where s_{igt} represents the revenue share of product g for firm i at time t. We perform an anlogous procedure for materials used in production; consequently,

$$q_{it} \approx \frac{\text{Revenue}_{it}}{P_{it}} \quad ; m_{it} \approx \frac{\text{Material expenditure}_{it}}{P^M_{it}}$$

We conduct separate production function estimations for every 626 industries at the 6-digit level present on the Chilean IRS records. Our sample selection is contingent upon having a minimum of 100 observations in each sector. Building on the approach outlined in Foster et al. (2022), our objective is to allow output elasticities to exhibit as much variation as possible within the same aggregate industry.

We successfully estimate production functions for 97% of firm-year observations within the 6-digit industries that meet the minimum data requirement. However, for the remaining 3% of firm-year observations, where data is insufficient, we extend our production function estimation to 160 sectors and 9 sectors. In Table 1, we present the mean material-output elasticities by different sectoral aggregations:

Table 1: Material-Output elasticities by granular of estimation

	6 digits	3 digits	2 digits	1 digit
Agriculture	0.683	0.666	0.664	0.639
Mining	0.610	0.593	0.593	0.624
Manufacturing	0.622	0.620	0.624	0.593
Utilities	0.575	0.599	0.612	0.603
Construction	0.615	0.576	0.576	0.583
Retail and Wholesale	0.662	0.620	0.624	0.651
Transportation and ICTs	0.610	0.619	0.619	0.540
Financial and Real Estate Services	0.525	0.527	0.527	0.561
Other Services	0.588	0.566	0.552	0.494

We document the evolution of markup moments over time in Figure 5. Additionally, we illustrate sector and labor heterogeneity in Figure 6.

Figure 5: Markup evolution in time

Panel A: Markups moments

Panel B: Markup different weights

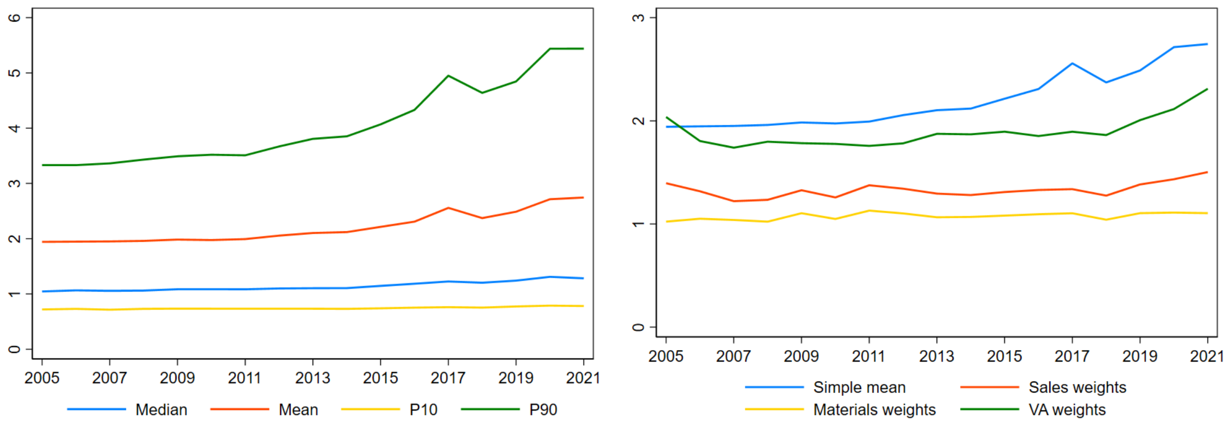
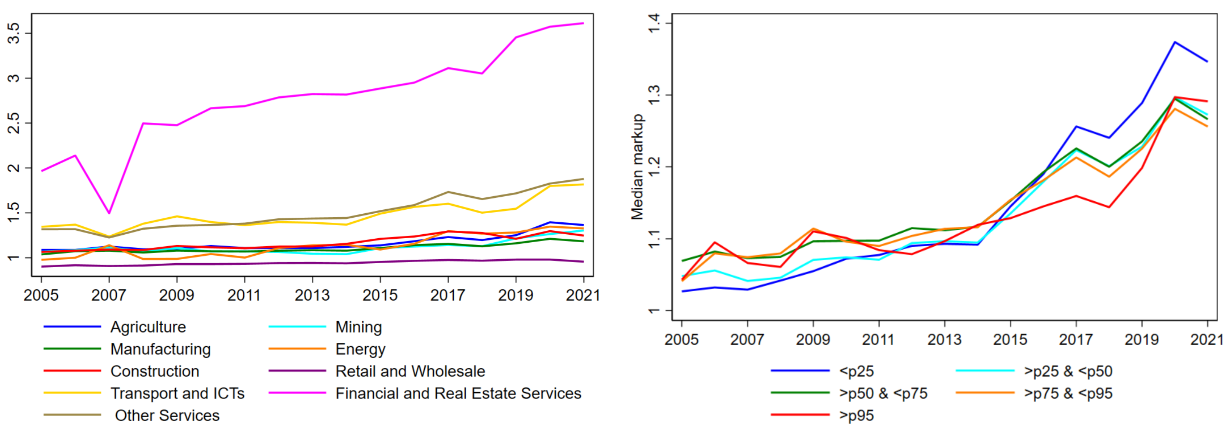


Figure 6: Markup heterogeneity by sector and firm size

Panel A: Markups by sector

Panel B: Markup by firm size



Note: Labor headcounts percentiles describe firm size.

C TFP growth robustness

Figure 7, Panel A presents the results of Total Factor Productivity (TFP) in a closed economy, while Panel B illustrates the TFP evolution within a production Input-Output structure across nine industries. In line with the findings of Baqaee and Farhi (2020), a significant portion of factor reallocation occurs between firms within sectors, resulting in limited reallocation between sectors. This suggests that TFP is primarily driven by the residual term, representing technological changes. This underscores the importance of having appropriate data to describe TFP changes at the firm level rather than using industry-level data.

Figure 7: TFP Closed economy

Panel A: Closed Economy

Panel B: TFP: Closed economy 9 sectors IO

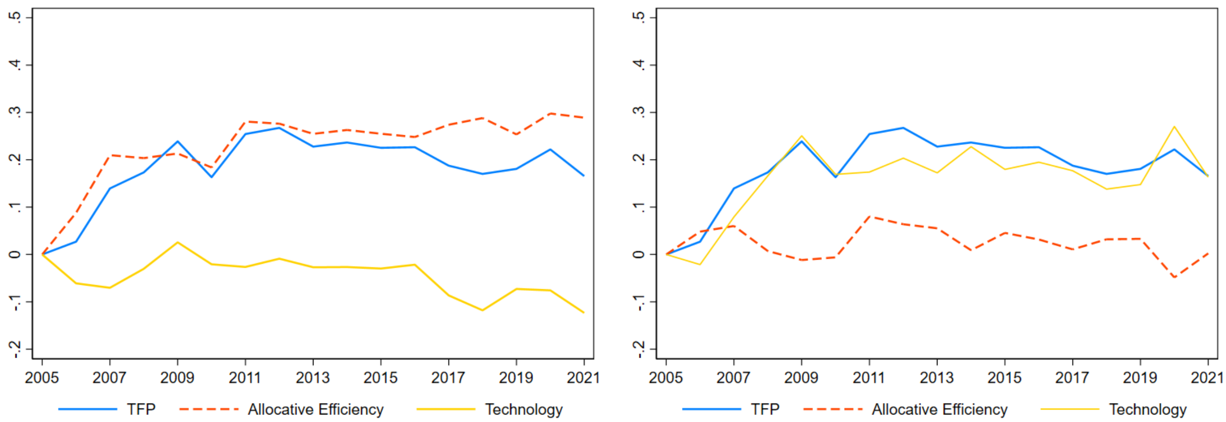
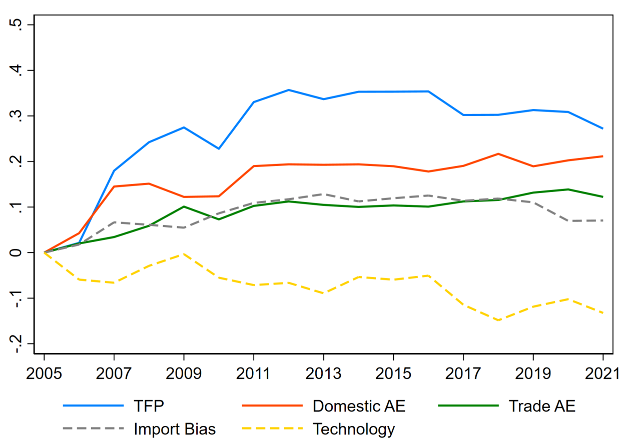


Figure 8: Benchmark
Percentage growth relative to 2005 levels



Notes: AE stands for Allocative Efficiency